Activity and Location Recognition Using Wearable Sensors

Using measured acceleration and angular velocity data gathered through inexpensive, wearable sensors, this dead-reckoning method can determine a user's location, detect transitions between preselected locations, and recognize and classify sitting, standing, and walking behaviors. Experiments demonstrate the proposed method's effectiveness.

Seon-Woo Lee
Hallym University, Korea

Kenji Mase
ATR Media Information Science Laboratories, Japan

Context awareness—determining a person's current location and recognizing what he or she is doing—is a key functionality in many pervasive computing applications. Location-sensing techniques are based on either relative or absolute position measurements.[1] Much of the current research in this area, described in the "Related Work" sidebar, uses absolute-measurement–based approaches (also called reference-based systems). However, using both relative and absolute methods, as robotics often does, is usually more effective in terms of cost and performance. The fundamental idea of the relative measurement approach is to integrate incremental motion information over time. This is known as *dead reckoning* or *odometry*.

We began our project to study the feasibility of applying the dead-reckoning method to recognize a person's location in indoor environments. We focused on detecting walking behavior, because human locomotion is achieved mainly via walking. If a system can recognize walking behaviors and count the number of steps, it can estimate a person's current location referenced on a known starting location. As a first attempt, we suggested a combined method involving a simple active beacon and dead reckoning that could track a person's location continuously with reasonable accuracy.[2] However, it also showed an inherent problem of dead reckoning—that heading errors cause large lateral-position errors. To avoid this problem, we developed a location recognition method based not on a description of motion in 2D space but on verbal descriptions of path segments, such as "walk straight, then go down the stairway, and turn right."[3] We obtained a promising result: 86.7 percent of the average recognition ratio (the number of correctly detected transitions divided by the total number of location transitions) for 12 transitions between 6 locations in an office environment. However, the method was limited in the case of a long path, because it determined transitions based on accumulated numbers of steps instead of a whole sequence; thus, it showed the location transition before the person reached the destination. In addition, the main source of error originated from misrecognizing the person's activity.

This article suggests an improved method to tackle these limitations. This involves

- Improving activity recognition by adding different types of sensors, finding an optimal sensor position on the body, or both
- Finding an appropriate descriptor for the relative displacement of the subject

The basic idea of our new approach has not changed: detecting a location transition by integrating the subject's motor activities.

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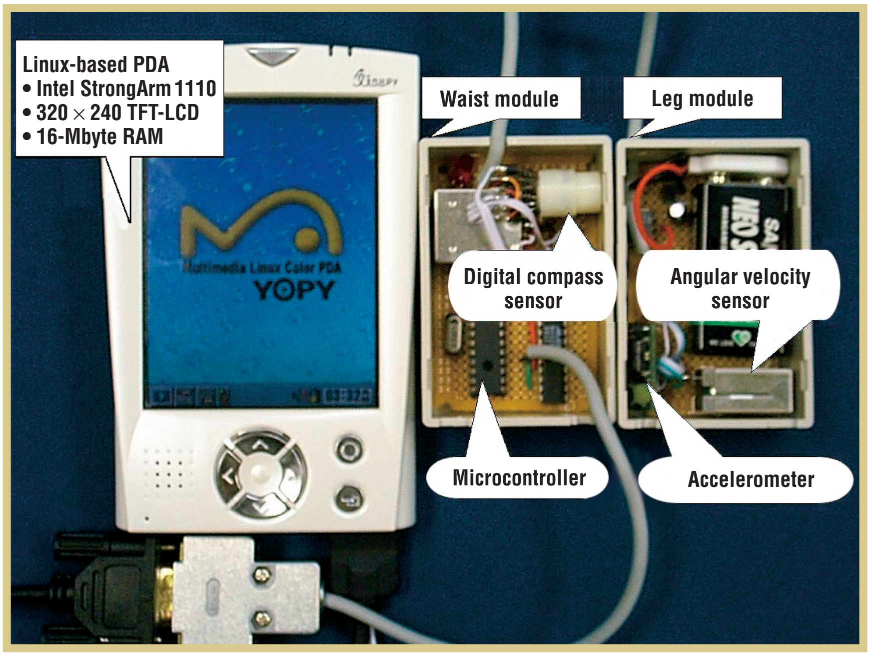

Figure 1. The proposed PDA and sensing module.

The system

To improve activity recognition, we modified the hardware, recognition method, and position of the sensors on the body. The system consists of a Linux-based PDA and a sensing module (see Figure 1). The PDA (YOPY from Gmate) has an Intel StrongArm SA-1110 CPU, 16 Mbytes of RAM, 32 Mbytes of flash memory, a 320 × 240–resolution TFT-LCD touch screen, and other peripherals.

The body-worn sensing module consists of an 8-bit microcontroller (the 10-MHz PIC 16F873 from Microchips), a biaxial accelerometer (ADXL 202EB from Analog Devices), a simple digital compass sensor (Digital sensor No.1490 from Dinsmore), an angular velocity sensor (Gyrostar ENV-05D from Murata), and other electrical parts, including a 9V battery, power regulator, RS-232 signal converter, and connector. The sensing module is implemented in two separate 50 × 35 × 75 mm boxes. Using these simple and wearable sensors, our methods detect the following predefined activities, called *unit motions*: *sitting*, *standing*, and three types of walking behavior—walking on *level* ground, going *up* a stairway, and going *down* a stairway.

We use a 3D position vector instead of a verbal sequence of unit motions as a new descriptor. When the system detects a walking behavior, the proposed location recognition method updates a current displacement vector using dead reckoning. The system then compares the calculated current vector with a location transition vector table that was built during a training phase. In the training phase, the system first requires a set of data to determine the parameters of the unit motion recognizer for the three walking behaviors. From this data, the unit motion recognizer can determine the parameters automatically. The system records unit motions and heading measurements while the user walks from one location to another. Using the recorded sequences, the system can easily build a location transition table. In the recognition phase, the system continuously tries to find unit motions and recognize a location transition from a known starting location.

Figure 2 shows the use of the sensing modules and the direction of a measurement obtained from each sensor. One box, the *leg module*, contains the biaxial

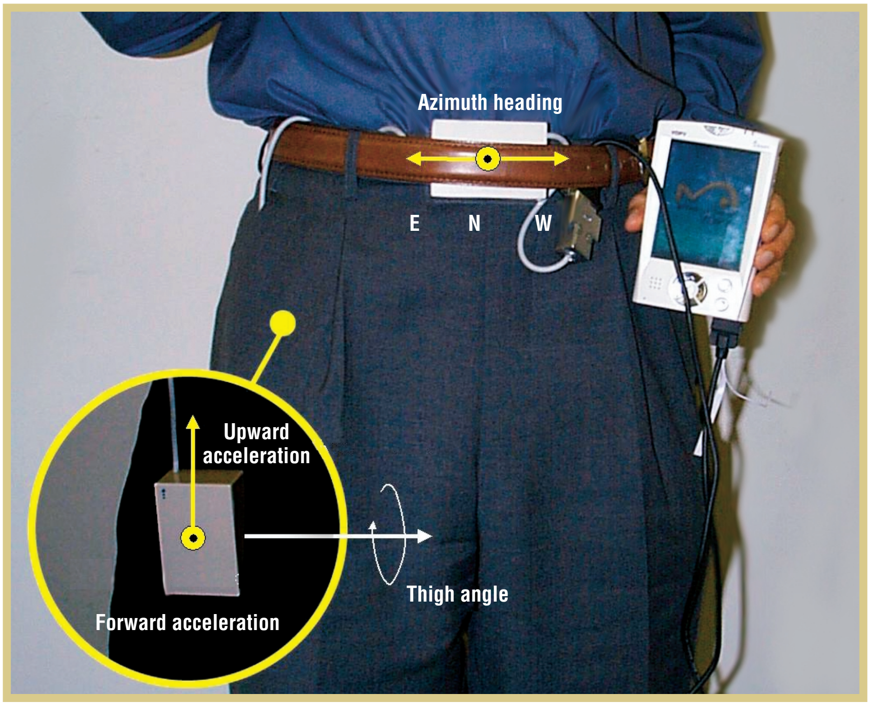

Figure 2. Use of the sensing module and the direction of each measurement.

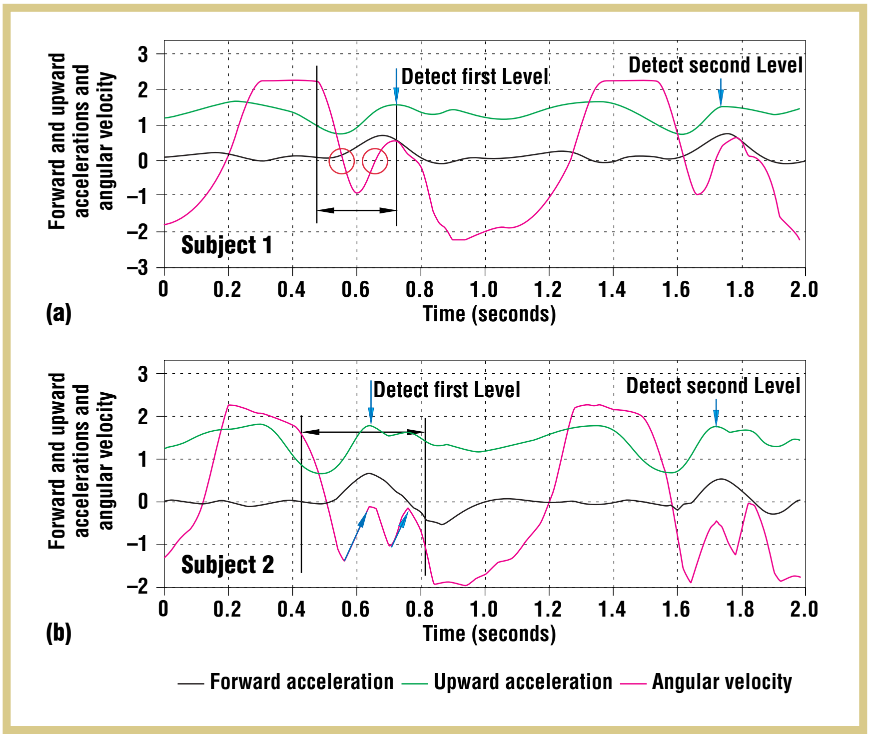

Figure 3. Typical trajectories of sensor signals for *level* walking behavior of two subjects (a) and (b).

accelerometer and the gyroscope. It is located in the user's right or left trouser pocket and measures the acceleration and angle of the user's thigh. We can easily estimate the leg module's degree of movement depending on the pocket's shape and size. We assume that the basic directions of measurements do not change—that the leg module is not turned upside down while it operates. In general, this condition could be satisfied for most kinds of trouser pockets. The second box, the *waist module*, is attached to the middle of the user's waist and detects direction as the person moves. After some experimentation, we concluded that these are the best positions for activity and location recognition; the system is also comfortable and provides unobstructed wearability.

The accelerometer in the leg module measures the forward and upward accelerations of the user's thigh, which are denoted by $a_x(t)$ and $a_z(t)$, respectively, where t stands for time. The acceleration signals are low-pass-filtered via a second-order elliptic digital filter with a 2.5-Hz cutoff frequency. The system measures the angle $\theta(t)$ of the user's thigh movement using a digital integrator of the angular velocity, $\dot{\theta}(t)$, obtained from the gyroscope.

The digital compass sensor can give us only the four azimuth headings (N, E, S, and W) as logic signals, which are read by the microcontroller's digital input ports. Using the 10-bit built-in analog-to-digital converter, the microcontroller reads the two acceleration and angular velocity signals every 20 milliseconds. It then sends the data to the PDA via a serial communication channel.

The proposed location recognition system has the same three function blocks (from the conceptual functional layer) used in our previous work: a sensing block (which starts at the bottom layer) a unit motion recognizer (at the middle layer), and a location recognizer (which ends at the top layer).[3] The sensing block reads the data from the sensors via the PDA's serial port and then executes a set of preprocessing tasks, including filtering and computing statistical properties. When the unit motion recognizer identifies one of the five predefined types of unit motion, the location recognizer calculates the current displacement vector by dead reckoning. Then, the location recognizer tries to find this location in a table containing other locations' relative displacements from a starting point. If it finds a matched location, it changes the user's current location. This process repeats with each new starting location.

Let's consider an example. A coffee maker is located somewhere away from the user's seat or office. First, the user goes to the coffee area to get a cup of coffee. We can describe these motor activities in terms of unit motions:

Path: standing → 2 steps north → 40 steps east → 3 steps south → 6 steps west

The transition vector from the user's seat to the coffee maker is (north: 2, east: 40, south: 3, west: 6). If the accumulated current descriptor matches the descriptor in the trained vector table, the system detects change in the user's location. We can compute the transition vector from the number of steps, with the heading as (–34, –1, 0), where one step size is 1, and the east and north headings are the x and y directions, respectively.

Unit motion recognition

The robust and reliable recognition of unit motion is important for both situation awareness and location recognition. We define the following values for unit motion recognition as a basic feature vector:

$$\{\sigma_x(t), \sigma_z(t), \sigma_\theta(t), \Delta\theta_1(t), \Delta\theta_2(t), \Delta\theta_3(t)\}, \tag{1}$$

where $\sigma_x(t)$, $\sigma_z(t)$, and $\sigma_\theta(t)$ are a standard deviation over 50 samples of the forward acceleration, upward acceleration, and the thigh angle, $\theta(t)$, respectively. The $\Delta\theta_{\{1,2,3\}}(t)$ are the past three angle differences when the angle direction changed. Each value

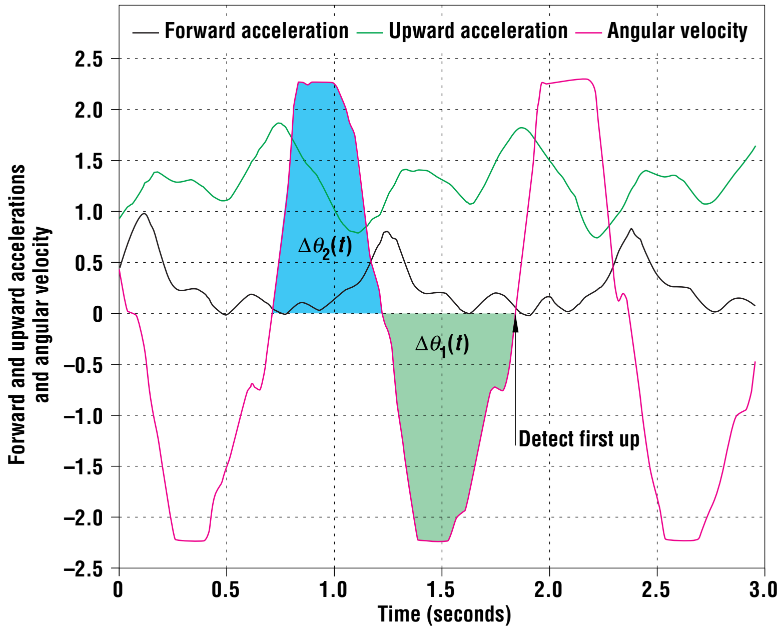

Figure 4. Typical trajectories of sensor signals for *up* walking behavior.

In contrast, for walking behavior, the system must not only recognize the user's activities but also count the number of steps. This means that the system must discriminate human walking in one cycle unit. In ergonomics,[4] one cycle of human walking (called the "gait cycle") is generally defined in terms of a time interval during which one sequence of a regularly recurring succession of events is completed.

To discriminate one cycle of level walking behavior, we use the positive peak value of upward acceleration $a_z(t)$ (denoted by blue down arrows in Figure 3). Using a conventional peak detection algorithm, the system tries to find the accelerations' positive and negative peak values. When it finds the positive peak of $a_z(t)$, the system tests the following conditions to determine a new level behavior:

1. $\sigma_x(t) > Th_{\sigma x}$ AND $\sigma_z(t) > Th_{\sigma z}$ AND $\sigma_\theta(t) > Th_{\sigma\theta}$, where $Th_{\sigma x,z,\theta}$ are threshold values for three feature values.
2. Whether the following feature value ≥ 2:

of the angle difference can be obtained from the integration of angular velocity in a time interval between zero crossings of $\theta(t)$.

Figures 3, 4, and 5 show the typical trajectories of two accelerations and an angular velocity for the three walking behaviors; they also show distinguishable characteristics in the sensor signals for the three walking behaviors, especially in the angular velocity changes. Based on this information, we derive the unit motion recognition process as follows.

We can easily recognize sitting and standing using the accelerometer to detect an absolute gravitational acceleration. When the following conditions are satisfied, the unit motion recognizer determines the subject's nonwalking behaviors:

- If $\sigma_\theta(t) > 16, \Delta\theta_1(t) > 70°, a_x(t) > 0.7\,g$, then the current activity is sitting.
- If $\sigma_\theta(t) > 16, \Delta\theta_1(t) < -70°, a_x(t) < 0.3\,g$, then the current activity is standing.

Here, g represents one gravitational acceleration. The proposed method can also recognize not only the activity but also the user's current status or pose.

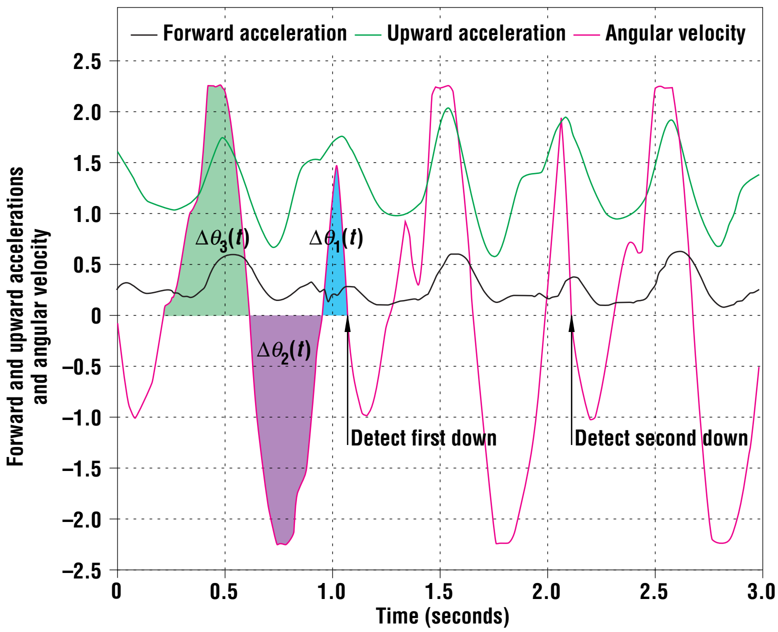

Figure 5. Typical trajectories of sensor signals for *down* walking behavior.

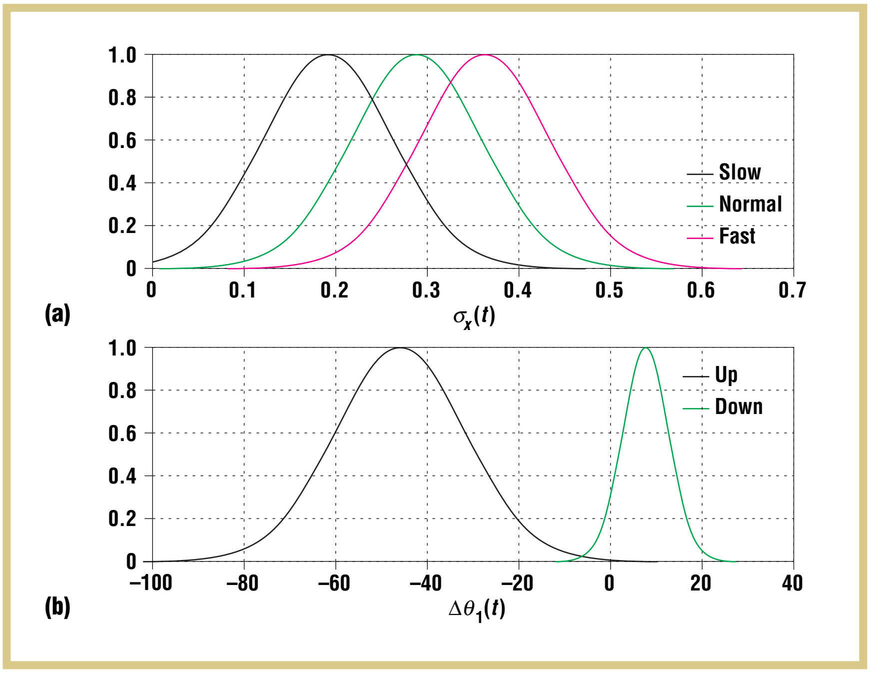

Figure 6. Membership functions of (a) input $\sigma_x(t)$ for level behaviors and (b) input $\Delta\theta_1(t)$ for up and down behaviors.

a. Find a number at the zero crossing (the red circles in Figure 5a) of $\dot{\theta}(t)$ in some interval.

b. If this number < 2, then the unit motion recognizer tries to find the number of angle changes (denoted by the blue upward arrows in Figure 5b).

Because we found two types of typical characteristics of sensor signals for many people, we have introduced two feature values for detecting a level behavior.

After detecting a level behavior, the unit motion recognizer tries to classify it into one of three subcategories: *slow*, *normal*, or *fast*. This more specific recognition of level walking behavior can help improve the performance of the proposed location recognition method. This classification technique is based on a simple fuzzy-logic reasoning method[5] with the following input vector:

$$\vec{u}_L(t) = \{u_1, u_2, u_3\} \equiv \{\sigma_x(t), \sigma_z(t), \sigma_\theta(t)\}. \tag{2}$$

We build a fuzzy rule base R_l^i for the three kinds of walking behaviors as follows:

If $[\sigma_x(t) \text{ is } M_x^i]$ AND $[\sigma_z(t) \text{ is } M_z^i]$ AND $[\sigma_\theta(t) \text{ is } M_\theta^i]$
Then the current level walking behavior is i,
where i can be slow (S), normal (N), or fast (F).

Here, M_j^i is a fuzzy set characterized by a membership function, which is defined as a Gaussian function:

$$\mu_j^i(u_j) = e^{-\left(\frac{\left(u_j(t) - m_j^i\right)}{\sigma_j^i}\right)^2}, \tag{3}$$

where $j = 1, 2, 3$ and $i = S, N, F$.

Using a Gaussian function as a membership function offers several advantages. First, we can easily adjust the fuzzy set's characteristics with its parameters. Second, if it is possible to get stochastic properties such as the mean and standard deviation from a set of sampled training data, we can use them to design the membership function. Therefore, we can describe a fuzzy set with paired numbers of mean and standard deviation values (denoted m/σ). For example, Figure 6 shows plots for membership functions of the fuzzy sets for (a) the input $\sigma_x(t)$ for level behaviors and (b) $\Delta\theta_1(t)$ for up and down behaviors.

Using the fuzzy rules and given input vector, we compute the truth values of each proposition as

$$\begin{aligned}
\omega_l^S &= \min\left(\mu_1^S(u_1), \mu_2^S(u_2), \mu_3^S(u_3)\right),\\
\omega_l^N &= \min\left(\mu_1^N(u_1), \mu_2^N(u_2), \mu_3^N(u_3)\right),\\
\omega_l^F &= \min\left(\mu_1^F(u_1), \mu_2^F(u_2), \mu_3^F(u_3)\right).
\end{aligned} \tag{4}$$

Here, we use the min operation as the AND operation in the fuzzy rules.

Recognizing the up behavior is also based on the fuzzy logic reasoning method. First, the recognizer tries to find the end of a cycle of up behavior when the angular velocity goes to positive near the moment of positive peak $a_z(t)$, as Figure 4 shows. At this moment, the recognizer performs the same fuzzy reasoning process to determine an up behavior. The input vector for the fuzzy reasoning is defined as

$$\vec{u}_U(t) = \{u_1, \cdots, u_5\} \equiv \{\sigma_x(t), \sigma_z(t), \sigma_\theta(t), \Delta\theta_1(t), \Delta\theta_2(t)\}. \tag{5}$$

From the same process, we can get a truth value with the given current input vector as

$$\omega^U = \min_{i=1,\cdots,5} \mu_i^U(u_i). \tag{6}$$

To recognize a down behavior, the unit motion recognizer per-

Related Work

Jonny Farringdon and colleagues and Kristof V. Laerhoven and Ozan Cakmakci have proposed interesting activity recognition methods that use accelerometers capable of distinguishing various human activities (sitting, standing, walking, ascending and descending a stairway, and so on).[1,2] We have suggested a recognition method not only to classify user activities but also to count steps, like a pedometer.[3]

Jeffrey Hightower and Gaetano Borriello have tried various systems, sensors, and techniques for indoor location sensing, because global positioning systems are unavailable in indoor situations.[4]

After Roy Want and colleagues developed an infrared-signal-based Active Badge system,[5] others studied many active-markers approaches. Recent work has suggested location-sensing systems that use an ultrasound time-of-flight lateration technique with radio frequency signal-based synchronization.[6,7] Instead of using an ultrasound signal, others suggested location sensing methods that use the RF signal strength as an indicator of the distance between a transmitter and a receiver on an already existing RF data network.[8,9]

Another approach is the use of a camera and natural or artificial passive markers. Hisashi Aoki and colleagues[10] developed a positioning system that uses a forward-looking, hat-mounted camera and a dynamic programming algorithm on a stand-alone PC. Brian Clarkson and colleagues suggested a similar system that uses a wearable camera and a Hidden Markov Model algorithm to recognize a user's spatial situation, for example, "entering or leaving an office."[11]

All of the systems described identify discrete events. In contrast, Wasinee Rungsarityotin and Thad E. Starner have proposed a system that uses an omnidirectional camera and a probabilistic algorithm to track a person's location.[12]

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forms fuzzy reasoning with a different set of input values whenever zero crossing of the angular velocity occurs. The input vector for down recognition is defined as

$$\vec{u}_D(t) = \left\{u_1, u_2, u_3\right\} \equiv \left\{\Delta\theta_1(t), \Delta\theta_2(t), \Delta\theta_3(t)\right\}, \tag{7}$$

and we can get a truth value as

$$\omega^D = \min_{i=1,\cdots,3} \mu_i^D\left(u_i\right). \tag{8}$$

The unit motion recognizer finds a maximum value from the obtained truth values ω^i, $i = S, N, F, U, D$ as defined in Equations 4, 6, and 8. When the maximum truth value is greater than a threshold value Th_f, the unit motion recognizer eventually determines the current step as one of the walking behaviors.

Location recognition

After the location recognizer has estimated the subject's current displacement, it tries to find a matched location in the location transition table, which has a set of relative displacements of other locations from a known starting point. This means that our location recognition method uses only a relative measurement for the user's location changes. We use a simple nearest-neighbor method to find a current location.

In our proposed location recognition method, we define the current displacement vector of the subject as a point in 3D space:

$$\vec{c}(k) = \left\{c_x(k), c_y(k), c_z(k)\right\}, \tag{9}$$

where k represents the time stamp of detection of a walking behavior.

When the unit motion recognizer detects a new walking behav-

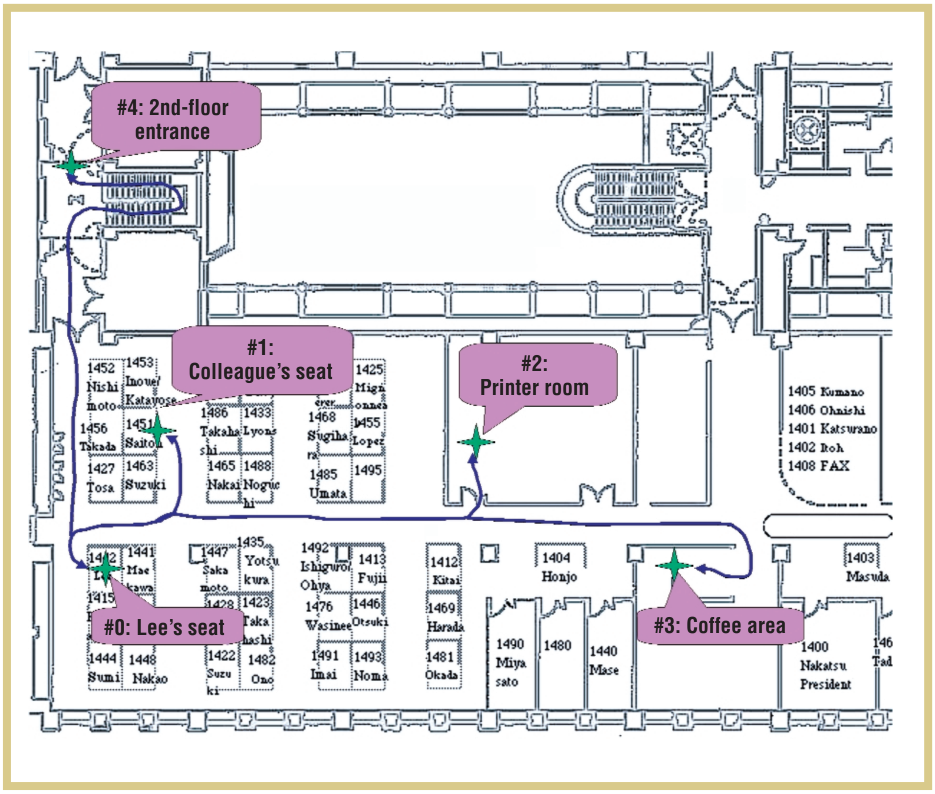

Figure 7. Location map showing the selected locations and paths.

ior, the location recognizer updates the displacement vector by adding the three axial components with the heading measurement

$$c_x(k+1) = c_x(k) + S_l \cos(2\pi A_h),$$
$$c_y(k+1) = c_y(k) + S_l \sin(2\pi A_h),$$
$$c_z(k+1) = c_z(k) + S_s, \tag{10}$$

where S_l represents a normalized stride length and S_s represents a normalized height of one stair (1 for up or −1 for down). A_h represents an azimuth heading obtained from the digital compass sensor. Because this sensor can provide only four azimuth headings, the A_h can be one of four values: $0.25\,n$, $n = 0, 1, 2, 3$ for west, south, east, and north, respectively.

The defined normalized stride length has the following values for recognized walking behaviors:

$$S_l = \begin{cases} 0.8 & \text{for slow} \\ 1 & \text{for normal} \\ 1.18 & \text{for fast} \\ 0 & \text{for up and down} \end{cases} \tag{11}$$

We obtained the values for slow and fast with respect to normal from the relationship between the stride length and speed derived in our previous work.[6] Even when the same user walks in free form, the stride length has some variances due to speed. Generally, if a user walks faster, the stride length increases. We chose the selected values from the linear model suggested in our previous work. To reduce the error caused by the variance of stride length, we use a specific slow, normal, or fast level behavior to estimate the current position.

Even though there is a horizontal component in the case of up and down behaviors, the major purpose of detecting those behaviors is to expand the working area into a multifloor environment that can be covered by the proposed method. In addition, if we consider the horizontal components of up and down behaviors, the misrecognition of such behaviors can also affect the x and y components. Therefore, we selected a zero stride length for up and down behaviors.

As we mentioned earlier, after updating the vector, the location recognizer tries to match it with a vector in the table. We define the location transition vector from location i to location j as the relative distance as follows:

$$T_i^j = \left\{ d_x^{ij}, d_y^{ij}, d_z^{ij} \right\}, \quad i, j = 1, \cdots, N, i \neq j, \tag{12}$$

where N is the number of locations trained and i represents a starting location. To find a matched location, we compare the distance between the current position and the transition vectors with respect to each component, then test whether the computed distances are less than each component of a threshold vector $Th_l \equiv \{th_x, th_y, th_z\}$. We test for

$$\left| c_x - d_x^{ij} \right| < th_x, \ \left| c_y - d_y^{ij} \right| < th_y, \text{ and } \left| c_z - d_z^{ij} \right| < th_z. \tag{13}$$

If the condition is satisfied, the recognizer eventually determines the transition from the starting location to the current location. Once the location recognizer determines the current location, the current position vector and the starting location are reset to zero and the changed location, respectively.

Experimental results

We tested the proposed method using a set of location transitions between selected locations in an office environment.

To evaluate the performance of the unit motion recognizer, we collected the walking data of eight subjects, two females and six males aged 23 to 51. They wore different types of shoes, such as sneakers, slippers, and high heels, and different types of pants,

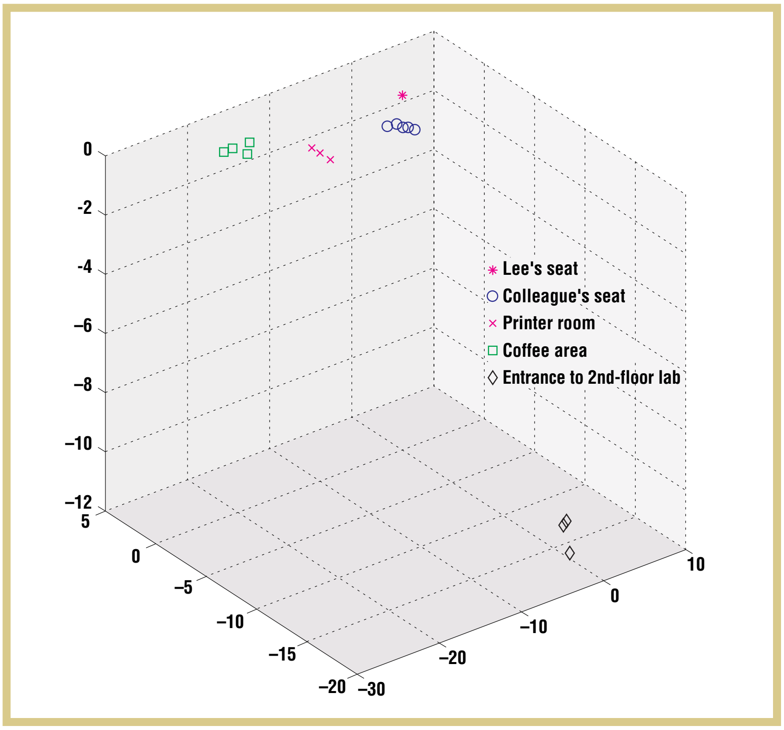

Figure 8. Relative displacement vectors from location 0 to locations 1 to 4.

For N given locations, we should build $N(N-1)$ location transition vectors to recognize the total number of paths. In our evaluation, we only built 10 transition vectors out of a maximum of 20 transitions, where N is 5. As Figure 8 shows, we can roughly see the real displacement of other locations from location 0. We can see some deviations for the same location: the error source is the incorrect estimation of stride length and heading detection. The heading error is most significant in terms of its influence on the current position. In our approach, we just use a relative measurement, because it does not require an absolutely accurate detection of the user's heading, just a reasonable repeatability.

We performed a set of location transition experiments with one subject to evaluate the method's performance. First, we used circular paths. We also tried a set of more complex paths such as $0 \rightarrow 1 \rightarrow$

such as jeans and slacks. For the training phase, each subject walked approximately 20 cycles of level behavior at three speeds and went up and down a stairway with 24 steps. Next, we collected test data as each subject walked on level ground for 90 meters and went up and down between two floors.

From the training data, the unit motion recognizer automatically extracts parameters such as threshold values and the mean and standard deviations of the sensor signals. Table 1 shows the parameters of the Gaussian membership functions of one subject (also shown in Figure 6). We can see that if a user walks faster, both feature values σ_x and σ_z increase. The threshold values used were

$$Th_{\sigma_x} = 0.08,\ Th_{\sigma_z} = 0.1,\ Th_{\sigma_\theta} = 2.5,\ \text{and}\ Th_f = 0.6.$$

Table 2 shows the average results of our activity recognition method for eight subjects. Recognition performance was satisfactory for counting steps as well as for classifying walking behaviors.

To evaluate the proposed location recognition method, we chose five locations (see Figure 7): Lee's seat (0), a colleague's seat (1), the printer room (2), the coffee area (3), and the entrance to the second-floor laboratory (4). These locations are often used in daily office activities. In the figure, solid blue lines denote paths between two locations.

From the three to five trials for one path (transition from location i to j), we built a location transition table for a subject with the average relative distance between the source and destination. Table 3 shows the obtained location transition table and threshold vectors for each path. For example, in Figure 8, we plot the distances from Lee's seat to all other locations.

TABLE 1
The mean and standard deviation values of membership functions for one subject.

Input	σ_x	σ_z	σ_θ	$\Delta\theta_1$	$\Delta\theta_2$	$\Delta\theta_3$
Level	m_1^i	m_2^i	m_3^i	–	–	–
Slow	0.211	0.191	12.99	–	–	–
Normal	0.236	0.288	11.92	–	–	–
Fast	0.269	0.363	12.05	–	–	–
Level	σ_1^i	σ_2^i	σ_3^i	–	–	–
	0.1	0.1	5	–	–	–
Up	m_1^U	m_2^U	m_3^U	m_4^U	m_5^U	–
	0.207	0.226	15.45	–45.78	38.88	–
	σ_1^U	σ_2^U	σ_3^U	σ_4^U	σ_5^U	–
	0.1	0.2	7	20	20	–
Down	–	–	–	m_1^D	m_2^D	m_3^D
	–	–	–	7.65	–24.48	25.11
	–	–	–	σ_1^D	σ_2^D	σ_3^D
	–	–	–	7	15	15

TABLE 2
Recognition ratios (%) of the unit motion recognizer for eight subjects.

Unit (%)	Level	Up	Down	Missing	Total number of steps
Level	95.91	0.51	0.67	2.92	978
Up	0	94.35	0	5.65	195
Down	0.51	0	92.85	6.63	199

TABLE 3
Location transition table for the selected paths.

Path	d_x^{ij}	d_y^{ij}	d_z^{ij}	(th_x, th_y, th_z)
0 → 1	–3.79	–3.07	0	(1.6, 1.6, 1.2)
0 → 2	–13.20	–2.85	0	(2.0, 1.6, 1.2)
0 → 3	–19.00	0.75	0	(2.5, 1.6, 1.2)
0 → 4	0.40	–15.97	–11.30	(2.5, 2.5, 4.0)
1 → 0	3.34	3.32	0	(1.6, 1.6, 1.2)
1 → 2	–10.50	0.50	0	(1.6, 1.6, 1.2)
2 → 0	12.40	2.65	0	(1.6, 1.6, 1.2)
2 → 3	–5.60	1.18	0	(1.6, 1.6, 1.2)
3 → 0	19.50	0.25	0	(2.5, 1.6, 1.2)
4 → 0	–2.73	14.63	10.33	(2.5, 2.5, 4.0)

TABLE 4
Results of running the location recognizer for four circular paths and two complex paths.

Path	Number of trials	Number of failures	Accuracy (%)
0 → 1	22	0	100.0
1 → 0	22	1	95.5
0 → 2	22	0	100.0
2 → 0	22	1	95.5
0 → 3	20	1	95.0
3 → 0	20	3	85.0
0 → 4	15	2	86.7
4 → 0	15	3	78.6
0 → 1 → 2 →0	16	1	93.8
0 → 2 → 3 →0	14	0	100.0
Average			91.8

2 → 0. As Table 4 shows, we obtained promising results, indicating an improvement from our previous approach even with minimal hardware and processing power. The total average recognition ratio for 10 location transitions was 91.8 percent.

The method was limited in the case of a long path. The proposed method is based on dead reckoning, so it has the same problem as our previous method: an accumulated error increases proportionally to the distance the user travels. As Table 3 shows, we selected bigger threshold values for longer paths. However, we think we can partially solve this problem by introducing more locations with smaller path lengths. This would mean that the location recognizer would achieve the accumulated error of zero more frequently.

The other limitation is that the proposed method is prone to drift—meaning that if the recognizer incorrectly determines a location transition from a starting location, the method will not be able to determine an appropriate location transition. This limitation is an inherent characteristic of all dead-reckoning-based location-sensing systems.

We believe that our proposed method can help enhance conventional methods based on absolute measurement, such as active-marker methods, in terms of accuracy, scalability, and cost. We would like to study ways to find an optimal combination of two measurements for better location sensing. We also plan to implement a pervasive device for inclusion in our environment. P

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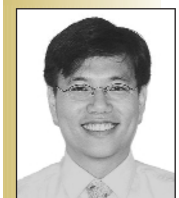
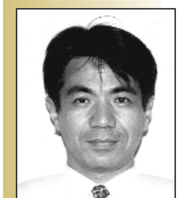
the AUTHORS



Seon-Woo Lee is an assistant professor of information engineering and communications at Hallym University. From 2000 to 2002, he was an engineer in ATR Media Information Science Laboratories, Kyoto, Japan. His research interests include context recognition, wearable and pervasive computing, real-time embedded systems, and robust control theory. He received a BS, MS, and PhD in electronics engineering from Korea Advanced Institute of Science and Technology. He is a member of the Korea Information Science Society and IEEE Systems, Man, and Cybernetics Society. Contact him at the Div. of Information Eng. and Communications, Hallym Univ., Okchun-dong, Chunchon-si, Kangwon 200-702, Korea; senu@hallym.ac.kr.



Kenji Mase is a group leader at the ATR Media Information Science Laboratories and a professor at Nagoya University. His research interests include gesture recognition, computer graphics, artificial intelligence, and their applications for computer-aided communications. He received a BS in electrical engineering and an MS and PhD in information engineering from Nagoya University. He is a member of the Information Processing Society of Japan, Virtual Reality Society of Japan, Institute of Image Electronics Engineers of Japan, Institute of Electronics, Information, and Communications Engineers of Japan, and ACM and a senior member of the IEEE Computer Society. Contact him at ATR Media Information Science Laboratories, 2-2-2, Seika-cho, Soraku-gun, Kyoto 619-0288, Japan; mase@atr.co.jp.